Automatic Detection of High Temperature Hydrogen Attack Defects from Ultrasonic A-scan Signals.

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ABSTRACT — **Successful application of the rich collection of classification algorithms to non-destructive testing signals depends heavily on the availability of adequate and representative sets of training examples, whose acquisition can often be very expensive and time consuming. In this paper, an out-of-service pressure vessel known to have lots of high temperature hydrogen attach (HTHA) defects is used to develop in a cost effective manner a database of ultrasonic A-scan signals. To test how adequate and representative these sets of A-scan signals are, a basic feature extraction method, coupled with a primitive classifier is shown to distinguish accurately the hydrogen attack from geometrically similar defects.**

Index Terms **— Nondestructive testing, signal processing, classification, feature extraction, ultrasonic A-scan database, hydrogen attack.**

I. INTRODUCTION

Studies have shown that manual ultrasonic inspection can be accurate but highly variable, depending on the inspection skills, training and emotional status or fatigue of the inspectors [1]. Many inaccurate inspections result from faulty instrument calibrations, inaccurate probe selection, or inaccurate interpretation of inspection results. The human factor when combined with variations in instrumentation, contribute to a lack of consistency in inspection results and interpretations. Considerable advancement in research and development in the last few decades has enabled nondestructive testing (NDT) to change from a "Black Smith" profession to an advanced multidisciplinary engineering profession. This has led to cost effective solutions of many challenging problems. Pipelines for instance, can now be screened without disturbing the production using intelligent tools such as pigging [2], guided wave ultrasound [3], phased arrays [4], etc…

In addition, the existence of cheap computing capabilities has led to the development of NDT techniques that rely heavily on the collection and processing of huge measurement data that eventually enhance operator interpretation. Automated ultrasonic detection and classification (AUDC) systems are thus becoming increasingly popular [5]. Motivation for the use of such systems arises from the need for accurate interpretation of large volumes of inspection data, and minimizing errors due to human factors. AUDC systems consist of three major parts namely pre-processing, features extraction, and classification. A number of supervised and unsupervised classification algorithms [6] such as K-mean clustering algorithm, fuzzy C-means, and more recently neural networks have been proposed for classifying signals. Using a suitable training algorithm, these networks can be trained to learn the correlation between features in signals and the type of reflector. However, the success of all such algorithms depends heavily on the availability of an adequate and representative set of training examples, whose acquisition is often very expensive and can be time consuming. For instance, application of ultrasonic techniques for high temperature hydrogen attack (HTHA) detection [7-9] requires a skilled ultrasonic technician with a good understanding of the mechanism of HTHA, and the ways it affects the propagation and scattering of the ultrasonic wave.

The objective of this contribution is to create a reliable database for HTHA from a retired pressure vessel known to have many HTHA defects, and to show that advanced signal processing techniques can aid NDT technicians to correctly identify HTHA from similar defects found in steels.

III. HIGH TEMPERATURE HYDROGEN ATTACK

HTHA is a metal degradation phenomenon that is well known to occur in carbon and low steels exposed to high partial pressure of hydrogen at elevated temperature. The source of hydrogen is the hydrocarbons in the flow steam. The damage is caused by the seepage of hydrogen that reacts with metal carbides to form methane gas. This reaction decarburizes steel, produces microcracks, and lowers the toughness of steel without necessarily producing a loss of thickeness.

Detection of HTHA is important to assure safe operation of pressure vessels and piping systems susceptible to such damage. Application of ultrasonic techniques for the detection of HTHA [7-9] requires high skilled technician with a good understanding of the mechanism of HTHA and how it affects the propagation and the scattering of ultrasonic waves.

There have been cases in the industry where inspectors have either missed HTHA or called it incorrectly [9]. Ultrasonic testing for this application is therefore not straightforward and requires a logical test methodology to detect HTHA. In the next section, a complete description of the data acquisition of ultrasonic A-scans obtained from a retired pressure vessel known to have many HTHA will be outlined.

II. DATABASE CREATION

An out-of service pressure vessel shown in Figure 1, with wall thickness 33 mm known to have many HTHA is used to collect RF A-scan signals for use in the Database. The data acquisition system consists of a SONATEST Masterscan 340 flaw detector, compression wave probes, couplant, and calibration blocks. The flaw detector has the capability of displaying and storing up to 100 RF A-scan signals. It also can transfer these signal to a PC via an RS 232 interface using the SONATEST Data Management Software (SDMS). A schematic of this data acquisition system is shown in Figure 2.

Figure 1: An out-of-service pressure vessel

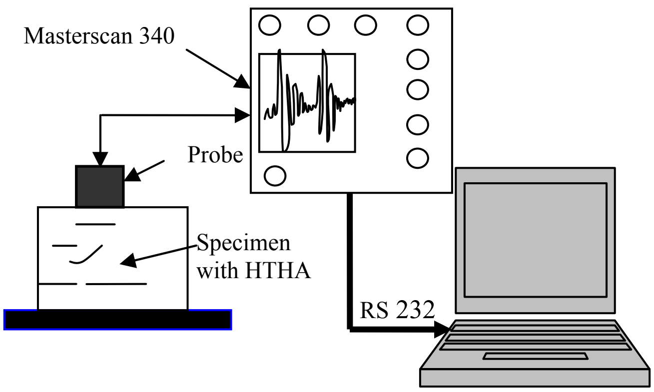

Figure 2: Data acquisition system used

After calibrating the flaw detector, the probe is placed on the outer wall of the 33 mm pressure vessel. A snapshot of the flaw detector screen is shown in Figure 3, where 5 HTHA defects are shown to be located within the pressure vessel wall thickness. The time-base of the flaw detector is zoomed to the region of defect 5 to isolate its A-scan signal from the rest of the defects. The result is shown in Figure 4.

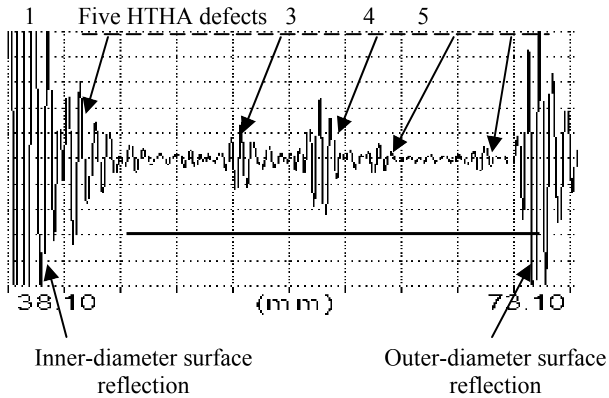

Figure 3: Snapshot of the flaw detector screen showing 5 HTHA defects located along the wall thickness.

The probe is now moved randomly around the detected defect to record as many A-scan signals as possible to cover all possible measurements that can be obtained for this defect when different operators are performing the test. Next, another HTHA defect is detected and all possible A-scan signals are recorded in a similar manner.

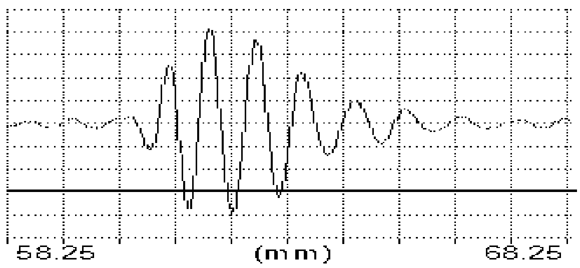

Figure 4: A snapshot of the flaw detector screen showing one HTHA defect

This process is carried on, and each time the A-scan signals are transferred to a directory in the Laptop using the SDMS software to create a HTHA databank of 400 A-scan signals.

To test the adequacy and the representativeness of the developed HTHA database, two other 400-A-scans databases of geometrically similar defects are created. These defects are lamination (LAM), and an artificial defect that consists of a flat-bottom hole (FBH).

IV. TESTS

The pre-processing stage here consists of removing the DC components, and normalizing all the signals to have the same energy. The feature extraction stage is based on the principal component analysis (PCA) technique [10]. This technique is used abundantly in all forms of analysis that range from neuroscience to computer graphics. This technique is a simple and a non-parametric method of extracting relevant information from confusing data sets. With minimal additional effort, PCA provides a roadmap for reducing a complex data set to a lower dimension in order to reveal the hidden, simplified structure that often underlies it. This hidden information is called feature. Next, the extracted features are presented to a priori trained classifier based on nearest-neighbor criteria to decide on which class the inputted A-scan signal belongs to.

The databases are organized in 4 sub-groups containing 100 A-scans each as shown in Fig.5.

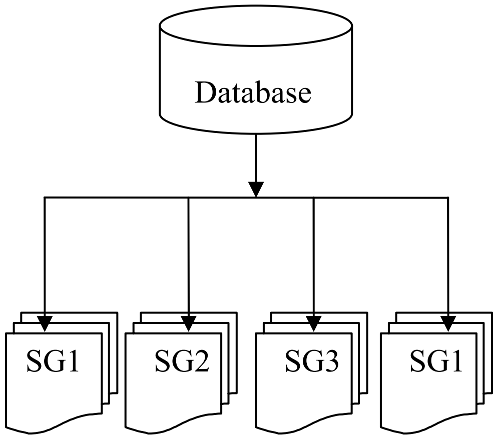

Figure 5: Organization of each database in 4 sub-groups of 100 scans each.

The AUDC system is first trained using 20 sets of A-scan for each class, and then tested by a set of 10 A-scans. The training sets are therefore picked randomly from each sub-group (from 100 A-scans), whereas, the testing sets are picked randomly from the remaining 80 A-scans of the same sub-group. This results in approximatively 1.6×10^{12} independent possible tests. The AUDC system is tested 500 times and the worst classification result is shown in the confusion matrix shown in Table I below.

Worst test		Classified as LAM	Classified as HTHA	Classified as FBH
True class	LAM	9	0	1
	HTHA	2	7	1
	FBH	1	•	9

Table I: Worst confusion matrix after 500 tests.

The worst case scenario is that for instance, out of 10 measurements, the lamination defect is detected and identified 9 times and missed once for the FBH. Similarly, the HTHA defect is detected and identified 7 times and missed twice for lamination, and once for FBH defect. Alternatively, it can be seen that LAM and FBH have 90% classification accuracy, whereas, HTHA has only 70% classification accuracy. The overall classification accuracy can be obtained by averaging the diagonal elements. Here 83.33% is obtained.

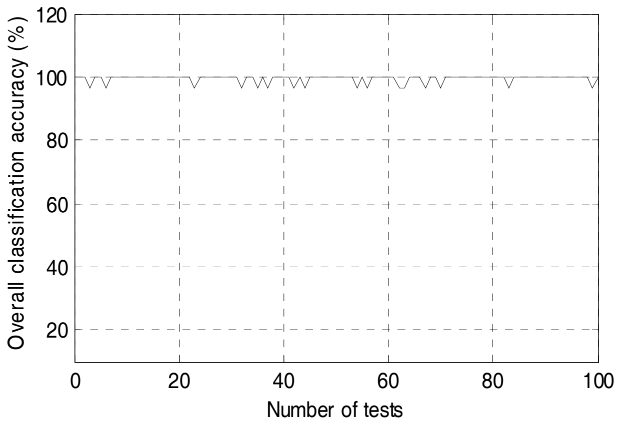

Figure 6: Overall classification accuracy for the three defects (average 99.46%).

The overall classification accuracy (average of the diagonal elements of the confusion matrix) is not affected much when the system is subjected to different tests. For 100 independent tests, the overall classification accuracy is shown in Figure 6. The average over these tests is 99.46%. For HTHA defect, the classification accuracy versus the number of tests is shown in Figure 7, which averages to 98.4%.

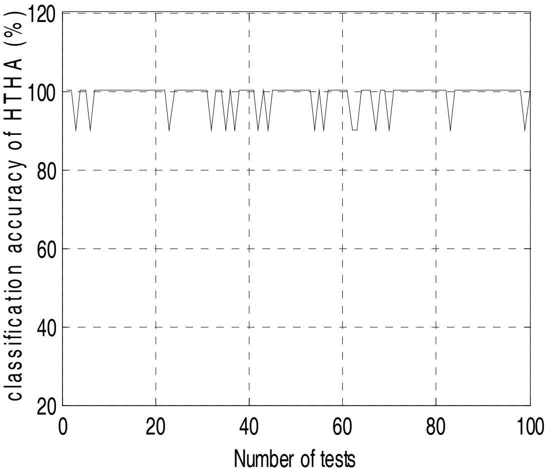

Figure 7: classification accuracy for the HTHA (average=98.4%).

V. CONCLUSION

In this contribution, it is shown that with a commercial flaw detector, a reliable database can be created. HTHA is accurately classified among geometrically similar defects using simple feature extraction technique coupled with a primitive classifier. Thus, it is shown that the availability of reliable database is vital for any AUDC system to give accurate results that can aid unskilled NDT operator to distinguish between challenging defects such as HTHA and defects such as stringers commonly found in pressure vessel and piping systems.

ACKNOWLEDGEMENTS

The authors wish to acknowledge the support of both King Fahd University of Petroleum and Minerals, and the King Abdul Aziz City of Science and Technologies (KACST), Saudi Arabia, to carry this research.

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